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INFLUENCES ON CELL PHONE BANKING ADOPTION IN SOUTH AFRICA: AN UPDATED PERSPECTIVE

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Abstract

The purpose of this paper is to revisit the question of what factors influence cell phone banking adoption in South Africa, in the light of an earlier study conducted by Brown, Cajee and Davis. Brown et al. found that in 2002 despite the availability of cell phone banking, very few bank customers were making use of it. Hence a survey was conducted amongst potential users, rather than actual users. In this study conducted in 2010, an updated cell phone banking adoption framework drawing from more recent literature was employed, and a cross-sectional survey was conducted amongst a sample of cell phone subscribers, a large proportion of whom were cell phone banking users, rather than just potential users. A total of 220 responses were gathered and the data were analyzed through partial least squares with structural equation modeling, as well as regression splines. The results show that utility expectancy and user satisfaction play a key determinant role in the adoption behavior of cell phone banking users in South Africa.

Keywords: **Cell phone Banking; Mobile Banking; South Africa; Technology Adoption; Structural Equation Modeling (SEM); Regression Splines**

INTRODUCTION

The rapid spread of cell phones in Africa has been lauded as a technological success story for the continent. South Africa has been at the forefront of this growth. From the initial launch of cell phone services in South Africa in 1994, subscriptions ballooned to about 14 million in 2002. By 2010 the numbers had exceeded the population with well over 50 million cell phone subscriptions [1,2].

Cell phone banking is an application of mobile commerce which enables cell phone users to perform financial operations (e.g. checking balances, funds transfer, beneficiary payments, etc.) on cell phones at any convenient time and place [3,4]. Cell phone banking services were launched in South Africa as early as 1998 [5]. One of the earliest academic studies on cell phone banking in South Africa was conducted by Brown et al. [1] in 2002, when at that time there were less than 100,000 active cell phone banking subscribers [5]. Towards 2010, the number of subscribers had reportedly risen to about 5.6 million, or 28% of total bank customers [6], a huge increase, although still a small proportion of total cell phone subscribers. The aim of this study was therefore to obtain an updated perspective on cell phone banking adoption in South Africa, given the changes that have taken place since 2002.

In this paper we extend the work of Brown et al. [1] in several ways. Firstly we draw from more recent research to develop an updated theoretical model concerning cell phone banking adoption. In order to analyze data we employ more sophisticated techniques beyond the ordinary linear regression method used by Brown et al. [1]. This study employs a two-phased approach. Firstly data is analyzed utilizing partial least square (PLS) with structural equation modeling, then secondly the factor scores computed through PLS analysis are used to develop a regression splines (RS) model.

The rest of the article is organized as follows: Section two discusses the conceptual model. In section three, the research methodology and data analysis are presented while section four provides the findings and section five the discussion. Section six presents conclusion, limitations and ideas for future research.

CONCEPTUAL MODEL

Since cell banking applications are for personal use, the conceptual model utilized in this article was derived from various studies on consumer behavior with respect to electronic and mobile commerce, including banking e.g., Brown et al. [1], Carlsson et al. [7], Cody-Allen and Kishore [8]. Gu et al. [9], Luarn and Lin [10], Luo et al. [11], Min et al. [12], Molla and Licker [13], Teo and Pok [14] and Zhou et al. [15]. Factors identified as strong influences on technology adoption in the aforementioned studies include user satisfaction, utility expectancy, effort expectancy, trust, cost, and facilitating conditions. Each of these concepts will be discussed in turn, and hypotheses formulated concerning cell phone banking in South Africa.

Usage Intention and Usage Behavior

Theories of technology adoption and acceptance often take as the dependent variable either technology usage intentions or actual usage, since usage intentions are taken as a good predictor of usage behavior [16]. In this study, both behavioral intentions and usage behavior are investigated, in contrast to Brown et al. [1] where only intentions were investigated. The limited number of cell phone banking users at the time of the Brown et al. [1] study mitigated against measuring actual usage behavior. Given that by 2010 there were estimated to be about 5.6 million cell phone banking users in South Africa [9], it was therefore feasible in this study to also measure usage behavior so as to test the following hypothesis:
H1: Usage Intention positively influences Usage Behavior with cell phone banking.

User Satisfaction

User satisfaction reflects the user attitude towards an information system (IS) and the convenience of and enjoyment obtained from using it [12]. User satisfaction is a key dimension of IS success, including e-commerce success [13,17], and even mobile banking success [18]. User satisfaction has been confirmed as a key influence on user intentions to continue using an e-commerce system [19], even in the South African context [20]. It is also feasible to investigate user satisfaction in a context where a technology has already been diffused, as is the case with cell phone banking in this study. Hence, the hypothesis supported is:
H2: User Satisfaction positively influences the Intention to Use cell phone banking.

Utility Expectancy

Factors such as relative advantage from innovation diffusion theory (IDT), perceived usefulness from the technology acceptance model (TAM), and performance expectancy from the unified theory of acceptance and use of technology (UTAUT) have all been confirmed as key influences on intentions to use cell phone banking [1] or mobile banking [10,15]. Min et al. [12] argue that for consumer-oriented technology such as mobile banking the related concept of utility expectancy might be

a more appropriate predictor. Utility expectancy is related to aspects such as enjoyment and quality of life, rather than efficiency and effectiveness which are associated with performance expectancy and perceived usefulness [12]. The following hypothesis is hence suggested:
H3: Utility Expectancy positively influences the Intention to Use cell phone banking.

Perceived usefulness has been shown to be a determinant of user satisfaction with e-commerce in South Africa [20], a relationship that could equally apply with utility expectancy. Since utility expectancy is associated with enjoyment and quality of life, it has a strong bearing on user satisfaction derived from the use of a technology [12]. Thus, the hypothesis supported is:
H4: Utility Expectancy positively influences User Satisfaction with cell phone banking.

Effort Expectancy

Effort expectancy is the perceived effortlessness of using a technology [21]. Effort expectancy is representative of concepts such as ease of use, complexity and perceived ease of use [16]. Effort expectancy has a positive influence on intentions to use mobile banking [9,10,12]. Therefore we hypothesize that:
H5: Effort Expectancy positively influences the Intention to Use cell phone banking.

Theories such as TAM and UTAUT postulate that effort expectancy (perceived ease of use) has an influence on performance expectancy (perceived usefulness) [16]. This relationship has been confirmed in the context of mobile banking [9,10,15], leading to the hypothesis that:
H6: Effort Expectancy positively influences the Utility Expectancy of cell phone banking.

E-commerce success literature makes the case that system quality (which encompasses effort expectancy) has an influence on user satisfaction [13,17]. In mobile banking studies this relationship has been found to hold too [18]. The hypothesis supported is:
H7: Effort Expectancy positively influences User Satisfaction with cell phone banking.

Trust

Gefen et al. [22] define the concept of trust as a set of trusting beliefs about phenomena such as e-commerce. Its importance to e-commerce was highlighted by Molla and Licker [13] who included it as a key dimension in their model of e-commerce success. In the context of mobile commerce Min et al. [12] and Li and Yeh [23] demonstrate its importance, as do Gu et al. [9] and Lee and Chung [18] for mobile banking specifically. Trust has been confirmed as influencing intention to use mobile banking [9], lending support to the hypothesis that:

H8: Trust positively influences the Intention to Use cell phone banking.

The relationship between trust and perceived usefulness of e-commerce was established by Gefen et al. [22] and confirmed in South Africa by Brown and Jayakody [20]. Gu et al. [9] showed this relationship to hold with respect to mobile banking, although Luo et al. [11] found it to be statistically non-significant.

The relationship between trust and utility expectancy has not been tested in any of these studies so it is postulated that:
H9: Trust positively influences utility expectancy of cell phone banking.

Trust enhances satisfaction with e-commerce [13], a finding confirmed by Lee and Chung [18] in the context of mobile banking. The hypothesis supported is:
H10: Trust positively influences user satisfaction with cell phone banking.

Facilitating Conditions

Venkatesh et al. [16] propose facilitating conditions as one of the core variables in the UTAUT model. Facilitating conditions refers to the organizational and technological support mechanisms made available to users [16]. Zhou et al. [15] demonstrate the influence of facilitating conditions on adoption of mobile banking, leading to the hypothesis that:
H11: Facilitating Conditions positively influence the Intention to Use cell phone banking.

Cost

The cost of technology is relevant to the level of usage and adoption in developing countries [24]. This is most significant when the technology is for use by individuals. A cell phone is a personal device in which the cost of its maintenance is an important factor for its usage [12]. Cost directly affects adoption of mobile commerce applications. Where the costs are low, it will encourage greater usage of the service [12]. Luarn and Lin [10] confirm that perceived high costs of mobile banking negatively influence intentions to use it. Thus we hypothesize:
H12: Lower perceived cost positively influences the intention to use cell phone banking.

RESEARCH METHODOLOGY

A cross-sectional survey through a judgmental sampling procedure was conducted for cell phone banking customers in South Africa. A deductive approach was used, as implied by the formulation of hypotheses in the previous section. The formulated hypotheses that constitute the research model (Figure 1) were tested using a two-phased approach.

In the first phase, partial least squares (PLS) structural equation modeling was employed to ensure the least squares estimation of the components model [25]. PLS analysis allows for theory confirmation and development by exploring the relationships between variables [26].

In the second phase, Multivariate Adaptive Regression Splines (MARS) was used to model the relationship between the response and predictor variables as a piecewise polynomial function that was obtained by dividing the range of each predictor variable into one or more intervals. This allowed the relative importance of factors to be estimated [27]. MARS is not a well-known technique in IS research, so will be elaborated on further next.

Multivariate Adaptive Regression Splines (MARS) was developed to overcome the disadvantages of linear regression models (LRMs). It is a method based on modern forms of statistical learning which are important for regression and classification [28]. The method is useful for high dimensional data, for fitting linear and nonlinear multivariate functions [29]. MARS models possess the capabilities to characterize the existence of relationships between explanatory and target variables that are impossible for other regression methods [30]. The procedure of MARS modeling involves the separation of the parameter hyperspace of explanatory variables into disjoint hyper-regions where a linear relationship is used to characterize the impact of predictor variables on the response variables within each of these hyper-regions [30]. Each point at which the slope changes between the different hyper-regions is referred to as a Knot. The set of knots in the MARS algorithm is used to generate the Basis Functions (Splines) that signify single variable transformations or multivariable interactions [30].

Hence, the MARS model obtains the form of an expansion in a spline basis function (BF) so that the number of BFs and the parameters restricted to each of the knots are determined by the data [29]. The advantage of MARS lies in its power and flexibility to model relationships (of some basic functions) so that additive and interactive effects of predictors can determine the target variable while allowing for separate additive contributions or different multivariate interactions [28,29].

This MARS capability entails the selection of suitable explanatory variables, and the elimination of the least useful explanatory variables, from the selected set, thereby building a model in a two-phase process: first forward and the second backward stepwise algorithms.

The forward MARS algorithm models by minimizing mean square error (MSE) across the model space while looking for combinations of variables and knot locations that could improve the model fit in a forward stepwise approach [30]. This algorithm preserves the knot and variable pairs that provide the best model fit, and adjusts the response by employing linear functions that are non-zero on one side of the knot [30]. After a variable is selected in the forward phase approach, the subsequent variables depend on the previous split of the parent basis function (i.e. splitting on one side of the knot). In the backward stepwise algorithm, the set of explanatory variables is reduced according to a residual sum of squares criterion in a reverse stepwise approach, while the optimal model is achieved based on a generalized cross-validation (GCV) measure of the MSE [30,31].

Data Collection

Measurement items on the questionnaire (Appendix A) were derived or modified from relevant studies such as Brown and Jayakody [20], Gu et al. [9], Venkatesh et al. [16], Marchewka, et al. [32] and Min et al. [12]. Where constructs were not previously operationalized and validated in previous studies, measurement items were formulated from other similar test items in literature, e.g. for utility expectancy. The survey instrument was validated through a pilot study. This study was aimed at the population of current cell phone banking subscribers in South Africa. The questionnaires were sent to targeted groups by post and e-mail. Data were gathered in 2010 from 220 participants consisting of students and workers from varied fields in South Africa.

Data Analysis

Firstly we identified the reflective and formative constructs in our model to prevent misspecification in the construct development as described by Freeze and Raschke [33]. Reliability and construct validity were analyzed to determine the consistency and regularity of the survey questions. For construct validity, confirmatory factor analysis was employed. Items that loaded as expected on their respective factors with no cross-loading were retained, others were dropped. All refined factors showed a clean loading (Appendix B). The Cronbach alpha was used to test for reliability. The reliability test was applied to each of the validated multiple-item constructs. All alpha coefficients were greater than 0.7 indicating solid reliability (Appendix C). The internal consistency of the constructs was confirmed to be satisfactory. The structural equation with partial least square was computed with data using Warp PLS (Version 3.0) and the model fit was assessed. It is recommended that the p values for both the average path coefficient (APC) and average R-squared (ARS) be lower than 0.05, while average variance inflation factor (AVIF) be lower than 5 [34]. The p values were, for APC <0.001, ARS < 0.001 and AVIF <5 (Appendix D).

To identify which of the factors was the most important predictor of cell phone banking usage, we used factors scores generated from PLS to compute a regression splines (RS) model (utilizing Salford System's MARS software 6.6). Since there are mediators and independent variables in the PLS model, we generated multiple MARS models, one for each mediator and independent variable. RS provides the means for determining the order of importance of the constructs in the generated predictive model. This is represented in the form of a construct importance vector whereby the most important construct in the model is assigned a relative score of

100%, and each construct that was not established to be a predictor is assigned a score of 0%.

RESULTS

Findings are reported in terms of firstly the sample demographics and cell phone banking usage patterns, followed by hypothesis tests based on the PLS SEM analysis, and then the relative importance analysis based on MARS analysis.

Sample Demographics

The gender distribution of the responses showed 40% were female while 60% were male. The largest age group in the data sample was 21-25 year-olds, who made up 48% of the sample. Participants younger than 20 years of age were few, as a result of the condition on the questionnaire which specified that participants must have a functional bank account, monthly income and be subscribed to cell phone banking services. The distribution by occupation consisted of 56% students and 44% workers from diverse fields of employment. The demographic profile is displayed in Table 1.

Cell Phone Services Usage

Cell phone banking services available in South Africa include accounting services, financial information display, and other services such as purchase of SMS bundles and air ticket payments. Accounting services consist of money transfers, insurance policy transactions, third party payments, and cheque book ordering, etc. while financial information services are items such as bank statement requests, SMS transactions, and balance enquiries among others.

The usage of these services was widely distributed. Of the sample gathered, 37.7% used money transfer, 42.8% used third party payments, 5.5% used insurance policy services, 5.5% used order cheque book transactions and 7.3% ordered a new PIN. SMS alert services for account transactions were used by 94.5% of the sample and SMS alerts for when there is an entry into online banking by a total of 86.8%.

Balance enquiries were used by 69.2% of respondents, and statement requests by 83.2%. 38% of the sample used exchange and interest rate services, while 72% used product information facilities. Cell phone banking services such as cell phone airtime top-up were widely used (65.9%). Also frequently used, were services such as purchasing SMS and data bundles (81.8% and 85.9% of respondents respectively).

Other cell phone banking services mentioned by respondents included purchase of MXit (a free instant messaging application popular amongst the youth and young adults in South Africa) products/services (e.g., 58.2% of participants indicated they purchased “Moola” - a MXit virtual currency).

The cell phone banking usage profile is shown in Table 2. The level and diversity of usage in 2010 shows a big increase over the status in South Africa in 2002. Brown et al. [1] reported that less than 6% of respondents in their study claimed to have used any cell phone banking service [1].

Table 1: Demographic profile.

	Frequency	**Percent**
Gender		
Male	132	60
Female	88	40
Age		
Under 20	2	1
21-25	106	48
26-30	49	22
31-35	33	15
36-40	15	7
41-45	8	4
46-50	3	1
51+	4	2
Monthly net income		
<R5000	93	42
R5001-R10000	39	18
R10001-R15000	27	12
R15001-R20000	29	13
R20001-R25000	20	9
>R25000	12	6
Occupation		
Student	123	56
Employed	97	44

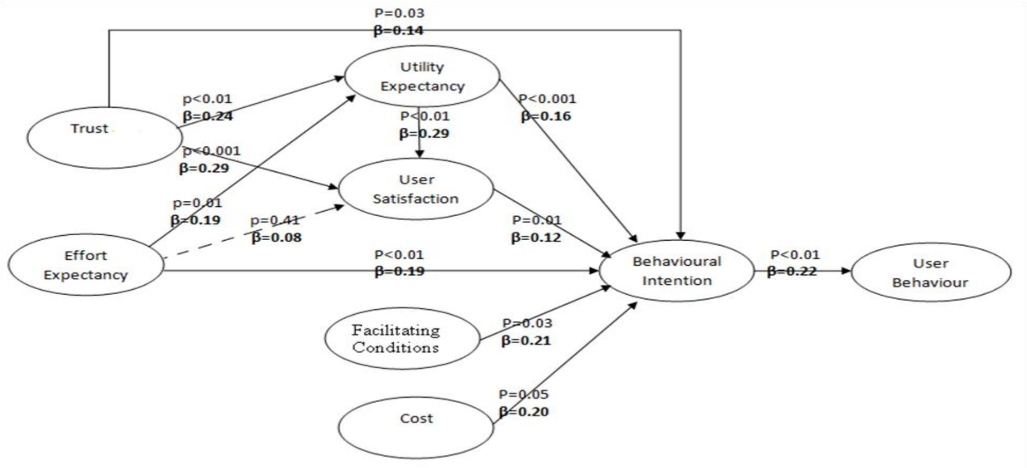
Table 2: Cell phone banking services usage profile.

	Percent
Accounting Usage	
Money transfer	37.7
Third party payment	42.8
Order new PIN	7.3
Order cheque book	7.3
Insurance Policies	5.5
Financial Information	
Balance enquiries	69.2
Statement request	83.2
SMS Alert (Account transactions)	82.2
SMS Alert (Online entry)	86.8
Exchange and Interest Rates	38
Product Information	72
Other Services	
SMS bundles	81.8
Data bundles	85.9
Cell Phone top up	65.9
MXit (e.g. Moola purchase)	58.2

HYPOTHESES TESTING

From PLS results as shown in Figure 1 below, all the hypotheses were supported except for hypothesis H7 - Effort expectancy positively influences User Satisfaction with cell phone banking. Effort expectancy nevertheless has an indirect influence on user satisfaction through utility expectancy.

Figure 1: Conceptual Model (PLS Path Coefficients).



Relative Importance of Factors

The results of MARs analysis to determine relative importance factor is shown in Table 3. With regards to predictors of Utility Expectancy, Trust and Effort Expectancy are the most important predictors while for User Satisfaction; it is Utility Expectancy that is the most important predictor. However, Trust also weighs heavily at 94.57%. An examination of the results in this table suggests that Utility Expectancy is the most important predictor (with 100%) for User Intention to adopt cell phone banking, followed by User Satisfaction with 72.43% importance. Facilitating Conditions, Cost, Effort Expectancy and Trust weigh in at 59.02%, 47.70%, 43.82% and 15.15% respectively (Table 3).

Table 3: Relative Importance of Factors.

Constructs	Utility Expectancy (UE)	User Satisfaction (US)	Usage Intention (UI)	Usage Behavior (UB)
Trust (TR)	100.00	94.57	15.15	
Effort Expectancy (EE)	100.00	56.41	43.82	
Utility Expectancy (UE)		100.00	100.00	
User Satisfaction (US)			72.43	
Facilitating Conditions (FC)			59.02	
Cost (CC)			47.70	
Usage Intention (UI)				100.00

DISCUSSION

In the Brown et al. [1] study, 94% of respondents had never used cell phone banking before. Relative Advantage, Perceived Risk, Banking Needs and Trial ability were identified as influences on their Intentions to Use cell phone banking. These factors provided strong predictive power as to behavioral intentions concerning a technology that had not as yet widely diffused. Perceptions of Relative Advantage were developed based upon banking customers comparing the new idea of cell phone banking to the more established ways of banking, e.g. computer-based Internet banking. The negative influence of Perceived Risk reflected the uncertainties related to performing financial transactions using what was commonly perceived as a communicative device. The influence of Banking Needs reflected how customers imagined their banking needs would be met through the use of a cell phone. Trial ability reflected their desire to be able to have hands-on experience of using the innovation before committing to usage. So, the model used by Brown et al. [1] was suitable for evaluating perceptions of potential adopters at the early stage of innovation diffusion, as was the case with cell phone banking in South Africa in 2002.

By 2010, adoption had matured to the stage where there were an estimated 5.6 million subscribers in South Africa. The Brown et al. [1] model was therefore not suitable for this user profile. The updated model was hence formulated, and included concepts such as utility expectation, user satisfaction, and actual usage behavior, which are appropriate amongst a sample of existing users of an innovation.

The findings confirm Trust and Effort Expectancy as major factors influencing Utility Expectancy. Trust and Utility Expectancy in turn have a significant influence on User Satisfaction. Utility Expectancy is the most important predictor of User Satisfaction followed by Trust. No significant relationship was found between Effort Expectancy and User Satisfaction. It may be that, as experience with cell phone banking grows, Effort Expectancy reduces in importance to such an extent that it is no longer an important consideration in determining levels of User Satisfaction. Nevertheless it has an indirect impact through Utility Expectancy. Trust, Effort Expectancy, Utility Expectancy, User Satisfaction, Facilitating Conditions and Cost are all found to have a significant influence on Intentions to Use cell phone banking. These findings are consistent with recent research on mobile banking adoption. Examination of the relative importance analysis shows that Utility Expectancy is the most important predictor of Intention to Use cell phone banking in South Africa.

CONCLUSION

There has been a rapid increase in the use of cell phone banking services in South Africa. Brown et al. [1] conducted a study in 2002, and found that less than 6% of respondents had used cell phone banking. In this study conducted in 2010, for some cell phone banking services (e.g. SMS alert services, bank statement requests), more than 80% of respondents had used them. Hence a conceptual model more suited to this stage of technology adoption was devised. This paper presents the updated and extended model of cell phone banking adoption in South Africa. It includes concepts such as user satisfaction and utility expectancy which are appropriate to measure when a technology is quite widely diffused amongst a target population. The updated model excludes concepts such as trial ability which were tested in the Brown et al. [1] model. Such concepts are appropriate when a technology has not yet been widely adopted, as was the case with cell phone banking in South Africa in 2002.

The paper makes a methodological contribution by demonstrating how MARS might be employed in addition to the commonly employed PLS SEM analysis. MARS enables the identification of the relative importance of factors influencing a dependent variable. Through the MARs analysis it was found that utility expectancy and user satisfaction are the key determinants of cell phone banking adoption in South Africa. This finding has implications for both research and practice. For practice it implies banks need to focus on improving the utility of cell phone banking and gauging customer satisfaction so as to sustain and increase the rate of adoption. For research it suggests that technology adoption researchers should perhaps shift focus from the TAM variables perceived usefulness and perceived ease of use to looking at factors such as utility expectancy and user satisfaction once a technology has widely diffused.

Future research can build on this study by establishing conceptual clarity between utility expectancy and user satisfaction. More rigorous measurement instruments can also be used for these constructs in the context of cell phone banking in a developing country.

Cell phone banking in South Africa has been predominantly adopted by the banked, most of whom already have access to banking channels such as computer-based Internet banking. Recent attempts have been made at reaching the millions of unbanked in South Africa through cell phone services such as M-PESA [35-37]. Unlike in Kenya and Tanzania, only modest success has been reported in South Africa with about 1.2 million M-PESA subscribers estimated since its launch two and a half years ago [35]. The M-PESA phenomenon presents a fertile area for future research, to understand why the pattern of diffusion of M-PESA differs across countries. In South Africa specifically the pattern of adoption of cell phone banking (or specifically M-PESA) amongst the banked and unbanked can be compared.

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